The Dynamics of Automobile Expenditures

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The views expressed herein are my own and not necessarily those of the Bureau of Economic Analysis or the US Department of Commerce

Motivation

- A central question in durable goods analysis: how much do consumers time their purchase decisions?
- We focus on three issues arising with temporal substitution
  1. The degree of temporal substitution and its main patterns.
  2. Are dynamic pricing strategies important?
  3. Do firms price discriminate?
- We analyze the automobile market
  1. Industry wisdom says consumers temporally substitute
  2. Seem to be large gains to temporally substituting
- With motor vehicles, have a unique window on timing of purchases
  1. detailed monthly price and sales vehicle data
  2. coordinated model-year cycle for motor vehicle
  3. demographic data

Overview of the Paper

1. Analyze how consumers time their new vehicle purchase decisions
2. Focus on decisions within the model year
   - choice set constant, but prices vary (decline)
   - clear tradeoff of enjoying vehicle now vs. waiting for price decline
3. Consumers modeled as an optimal stopping problem
4. Estimate parameters in consumer's indirect utility function
5. Results:
   (a) Consumers are price sensitive and willing to time purchases
   (b) Temporal substitution typically several times larger than cross-sectional substitution or entry/exit.
   (c) Dynamic pricing strategies matter.
   (d) There is significant price discrimination.

Literature review

1. Durable goods - infrequently purchased
   - (closest) Gowrisankaran and Rysman (2007) - DVD players
   - Carranza (2003, 2006), Song and Chintagunta (2003), Gordon (2006) and Nair (2005)
2. Non-durable goods - frequently purchased (grocery retail data)
   • impact of high/low pricing and other optimal pricing schemes, Slade (1998), Aguirregabiria (1999), Pesendorfer (2002), Erdem et al (2003), Hendel and Nevo (forthcoming).
3. Automobile pricing: incentives, dealer inventories, price cues (Zettelmeyer et al (2003,2006,2007).
4. Macroeconomic issues
   - aggregate inventory behavior: Hall (2000) and Attanasio (2000)
   - GDP volatility: Ramey and Vine (2007)

Talk Outline

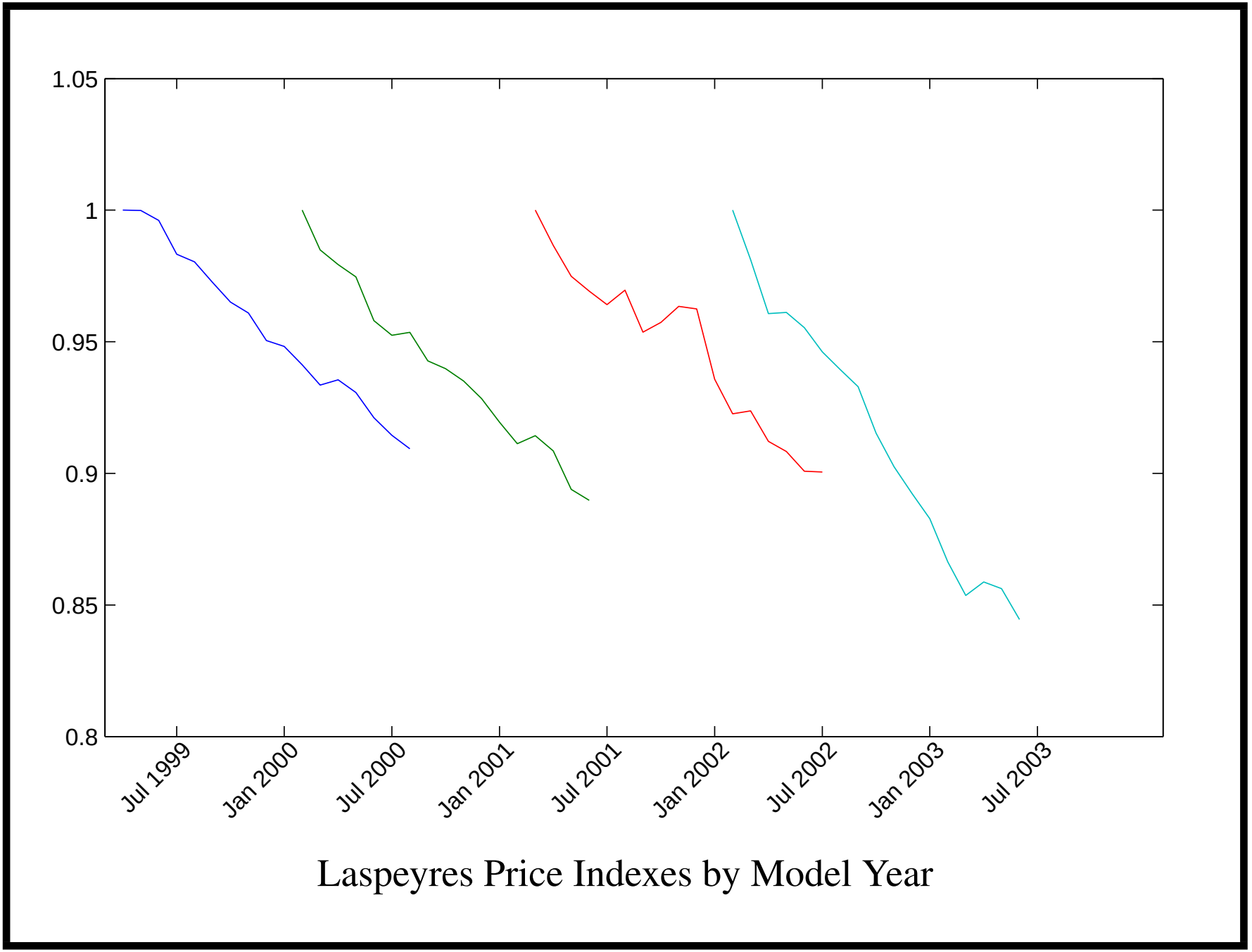
1. Data
2. Model
3. Results

Data - Combined 2 data sets

1. First: Power Information Database (PIN), from JDPA
   - Collected from dealerships, 15-20% of all U.S. retail sales.
   - Monthly observations by model/model-year from 1999 to 2003
   - Observe price, cash rebate, and financial details
   - Observe model-year distribution of sales by model
2. Second: Wards Communications - US monthly sales by model.
3. Combine both data sets to get:
   - Monthly series of sales by model & model-year,
   - Monthly series of real market prices by model & model-year,

Data Facts

1. Prices fall over the model year at 9% annual rate
2. Mean income of new vehicle purchasers falls over model year
3. Model-level sales are hump-shaped
4. Aggregate sales volatile

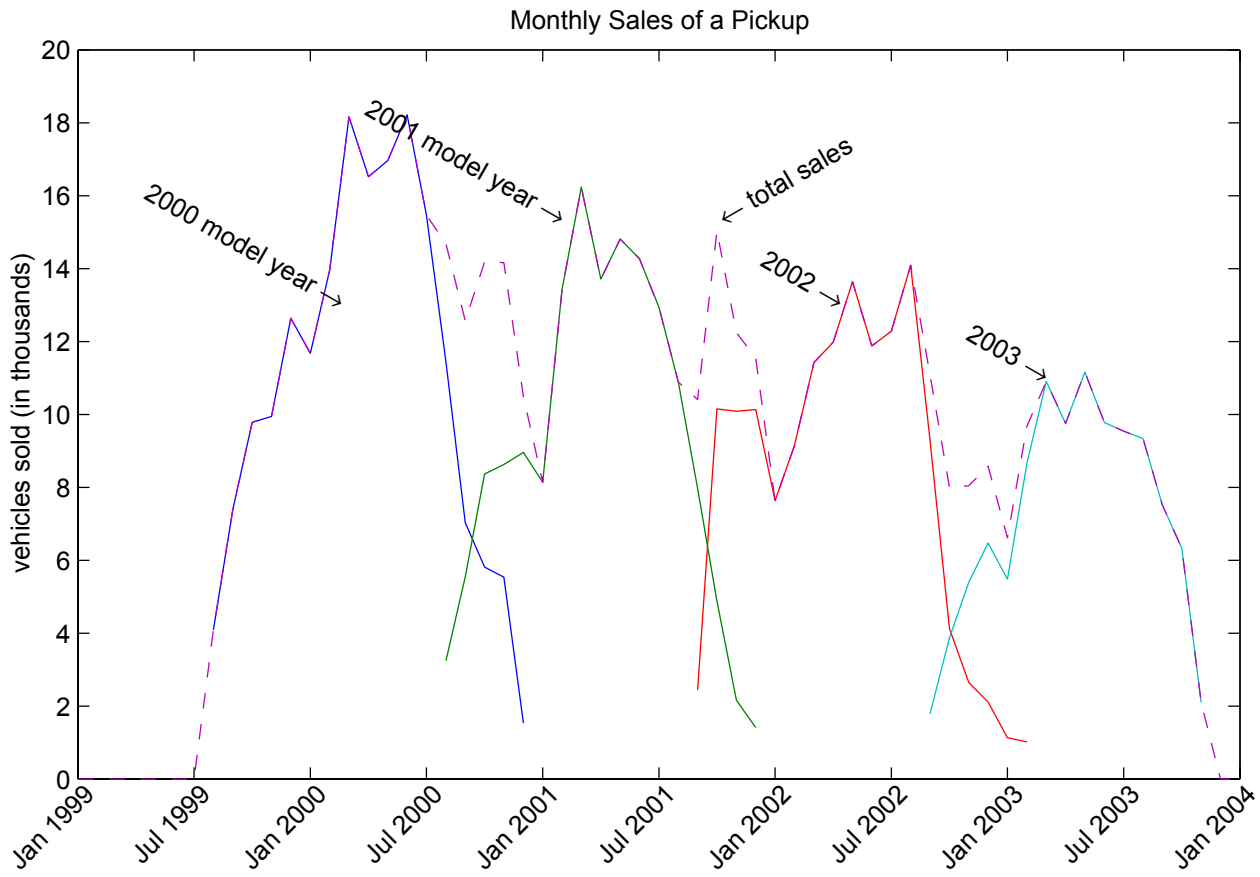


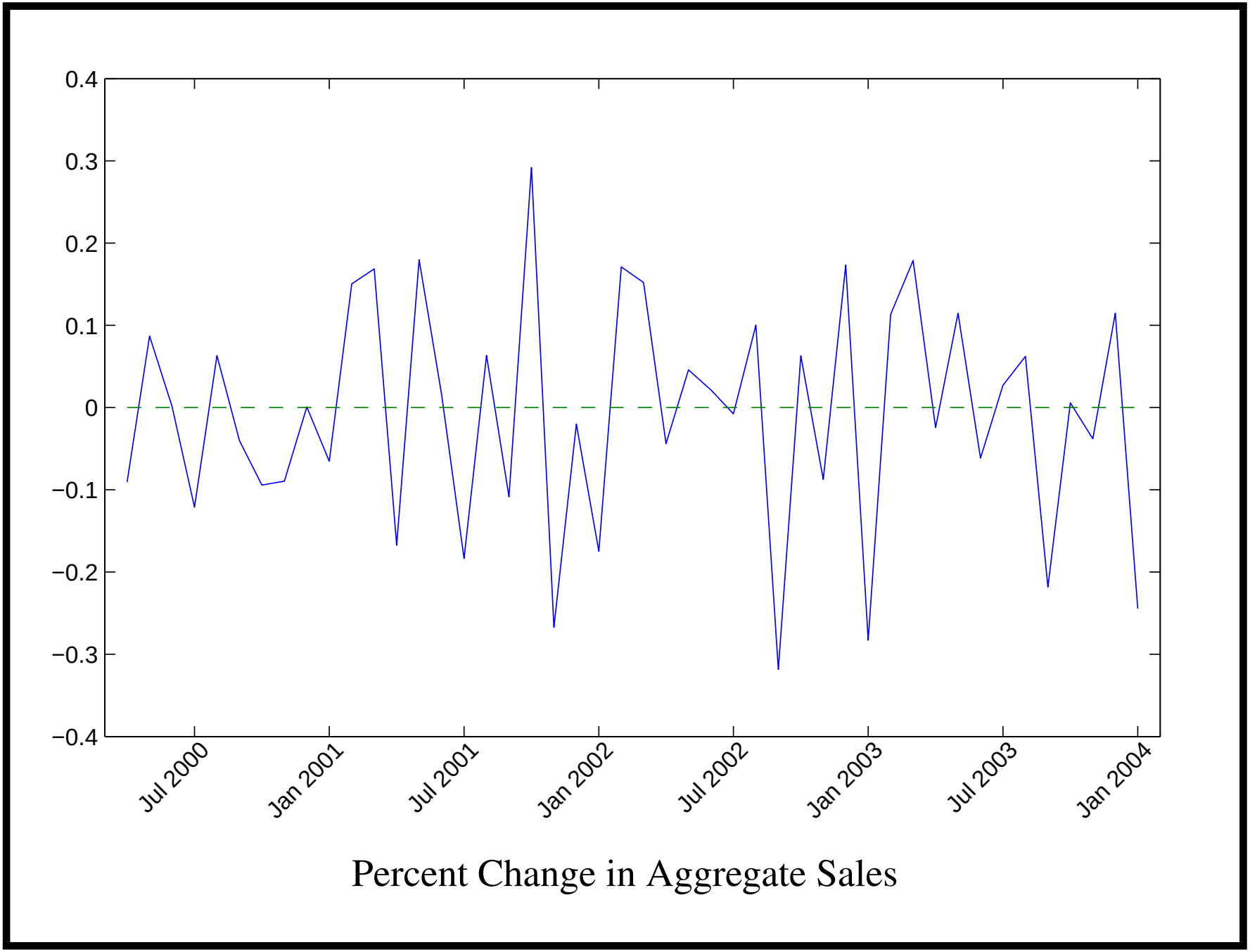
Laspeyres Price Indexes by Model Year

Data from Aizcorbe-Bridgman-Nalewaik 2007

	Income (thousands of dollars)
Quarter	Data
1	74.973
2	73.075
3	71.460
4	68.603

Average Income of New Vehicle Purchasers


Monthly Sales of a Pickup
vehicles sold (in thousands)
0
2
4
6
8
10
12
14
16
18
20
Jan 1999
Jul 1999
Jan 2000
Jul 2000
Jan 2001
Jul 2001
Jan 2002
Jul 2002
Jan 2003
Jul 2003
Jan 2004
2000 model year
2001 model year
total sales
2002
2003



Percent Change in Aggregate Sales

Reduced form analysis of prices and sales

- Is there positive correlation between p_{t-1} and s_t?
- First stage: detrend $\log(p), \log(s)$ by model
- Second stage: $\hat{s}_t = \Gamma_0 \hat{p}_t + \Gamma_1 \hat{p}_{t-1} + \Gamma_2 \hat{p}_{t-2} + \Gamma_3 \hat{p}_{t-3} + \Gamma_4 \hat{p}_{t-4} + \varepsilon_t$

variable	coefficient	estimate	NW s.e.
$\hat{p}_t$	Γ_0	-0.0069	0.2415
$\hat{p}_{t-1}$	Γ_1	-0.2029	0.2256
$\hat{p}_{t-2}$	Γ_2	0.0254	0.2150
$\hat{p}_{t-3}$	Γ_3	0.6265	0.2235
$\hat{p}_{t-4}$	Γ_4	0.4405	0.2018

Table 1: Coefficient Estimates from Sales Residual Regression

Model: Optimal stopping problem within Model Year

- All consumers show up at the beginning of the model year.
- Every month, each decides whether to buy a new vehicle or wait.
- In last month of the model year, waiting means not buying a new vehicle that model year.
- Remainder of income goes towards alternative consumption good.
- Aggregate across consumers to get predicted market shares
- Employ discrete-choice framework (BLP-style), includes
  - Consumer heterogeneity
  - Product differentiation

Dynamic Model

- if purchase: get utility (person i, good $j \in J$, month $t \in T$):

$$u_{ijt} = X_{jt}\gamma + \zeta C_t + \xi_{jt} - \beta^{T-t}\frac{\eta}{y_i}p_{jt} + \sum_{k=1}^{K}\sigma_k \nu_{ik} x_{jk} + \varepsilon_{ijt}, \qquad (1)$$

- β is discount rate (exogenous)
- Price discounted as if paid in last period of the model year
- Separates consumption of alternative good from timing of the vehicle purchase (perfect smoothing assumption)

Dynamic Model – value functions

- Value function in last period

$$V_{iT} = \max\left\{\pi_{iT}, \max_{j\in J}\left\{u_{ijT}\right\}\right\}. \tag{2}$$

  where π is utility flow from outside option (set to zero)

- Value function for $t \in \{1,\ldots,T-1\}$

$$V_{it} = \max\left\{\pi_{it} + \beta E[V_{i,t+1}], \max_{j\in J}\left\{u_{ijt}\right\}\right\}. \tag{3}$$

- Expectations only over taste-for-variety term
- Perfect foresight: choice set, characteristics, prices

Moment conditions & instruments

- GMM approach with 2 sets of moment:
  1. regular BLP moments: $E[\xi|X] = 0$
  2. additional moments: average income of purchasers by quarter
- Problem with correlation between ξ and prices
  - Firms and consumers see ξ. Higher ξ likely implies higher price, violating moment condition.
  - Usual instruments are competing vehicles characteristics. In equilibrium, $\text{char}_j \rightarrow p_j \rightarrow p_k$ and assume char_j are exogenous, so uncorrelated with ξ_k. *But has little power here.*
  - Use aggregates of other vehicles' inventory holdings: $\text{inv}_j \rightarrow p_j$ and $p_j \rightarrow p_k$. Assuming that inv_j is uncorrelated with ξ_k.
  - Use sum of inventories across all other manufacturers, all other vehicles in the same market segment, and all other vehicles produced by the same manufacturer.

Identification & Measurement

Because of the parametric assumptions on indirect utility, technically the model is identified (have to worry about multicollinearity of characteristics).

$\rightarrow$ caveat: is there a unique solution to the double loop iteration?

But what's the variation in the data driving the estimates?

1. Across model-years, have changes in the choice set over time with corresponding changes in sales.
2. Within a model-year, have changes in instruments (relative prices) and corresponding changes in sales.
3. Income moments are essential to pin-down distaste-for-price parameter

Estimation strategy

I use a simple variation on the estimation strategy detailed in Gowrisankaran & Rysman (2007).

Table 2: Parameter Estimates

Parameter		Dynamic Model	
Mean	Constant	-36.240	(1.803)
	Acceleration	-15.565	(2.328)
	Miles per dollar	-32.576	(6.823)
	Height	3.798	(0.392)
	Size	-12.969	(6.521)
Variance	Constant	28.844	(1.103)
	Acceleration	46.104	(3.552)
	Size	0.947	(12.162)
	Height	8.716	(0.997)
Variety		7.953	(1.685)
Model-year trend	ζ	-0.473	(0.240)
Distaste-for-price	η	12.415	(0.357)
Observations		9,485	

Quarter	Data	Model
1	$74,973	$75,423
2	$73,075	$72,882
3	$71,460	$70,678
4	$68,603	$69,093

Table 3: Average Income of New Vehicle Purchasers

Table 4: Own Price Elasticities for the 2002 Model Year (absolute value)

Market Segment	Dynamic Model Quartiles 1/4	1/2	3/4
Midsize	1.91	3.10	5.03
Pickup	2.45	4.61	5.38
SUV	2.71	3.82	6.24
Compact	4.21	6.35	7.20
Sporty	2.65	4.13	6.75
Fullsize	1.71	1.76	1.96
Upscale	2.60	3.61	12.37
Vans	2.41	3.01	3.93
Average	2.58	3.80	6.11

Table 5: Within Market Segment Cross-Price Elasticities for the 2002 Model Year

Market Segment	Dynamic Model		
	Min	Mean	Max
Midsize	-0.0012	0.0023	0.1239
Pickup	-0.0013	0.0066	0.1480
SUV	-0.0017	0.0018	0.1488
Compact	-0.0017	0.0145	0.0931
Sporty	-0.0004	0.0002	0.0220
Traditional	0.0000	0.0015	0.0069
Upscale	-0.0004	0.0012	0.0455
Vans	-0.0004	0.0016	0.0225

note: Statistics are computed only over vehicles within the same market segment.

Notation: M total market size, s market share, p is price.

Static model cross-price elas. formula:

$$\frac{ds_j M}{dp_k}\frac{p_k}{s_j M} = \frac{ds_j}{dp_k}\frac{p_k}{s_j} > 0. \tag{4}$$

Dynamic model cross-price elas. formula:

$$\frac{d(s_{jt}M_t)}{dp_{k,t+n}}\frac{p_{k,t+n}}{s_{jt}M_t},$$

where n is an integer. Expanding and canceling terms, we get

$$\frac{ds_{jt}}{dp_{k,t+n}}\frac{p_{k,t+n}}{s_{jt}} + \frac{dM_t}{dp_{k,t+n}}\frac{p_{k,t+n}}{M_t}. \tag{5}$$

Three counterfactuals

1. A temporary price discount by GM on pickups, holding all else constant
2. A temporary price discount by GM on pickups, allowing for best-price responses
3. All firms collude to not offer incentives

Table 6: $1,000 Price Discount for GM Pickups in month 6

Month	Chrysler	Ford	GM	Toyota	All Others	Outside
Total unit sales: difference between data and counterfactual						
6	-535	-888	26,012	-154	-594	
7	-580	-1,015	-974	-157	-668	
8	-554	-986	-1,056	-152	-651	
9	-567	-1,066	-1,058	-176	-720	
10	-576	-1,101	-1,144	-169	-749	
11	-566	-971	-1,129	-179	-772	
12	-649	-1,159	-1,071	-193	-873	
Total	-4,026	-7,187	19,580	-1,180	-5,026	-2,161

Estimating best-price responses

- Assume GM is price leader for pickups
- d_j denotes price incentives on pickup j, d_{GM} is average price incentive on GM pickups, and m is monthly trend
- inv_j are inventories of vehicle j, included to capture aggregate shocks.
- Estimate regression:

$$d_{jt} = \rho m_t + \omega inv_{jt} + \sum_{i=1}^{J} I_{v_t=j}\alpha_j + \sum_{k=1}^{5} I_{c_t=k}\left(\iota_j \bar{d}_{GM,t} + \kappa_j \bar{d}_{GM,t-1}\right) + \varsigma_{jt}, \tag{6}$$

- α are model fixed effects, (ι, κ) estimated for each company

Table 7: Predicted Incentive Responses to $1,000 GM Incentive

	Month		
	6	7	8
GM	1,000	0	0
Chrysler	476	292	0
Ford	508	310	0
Nissan	46	399	0
Toyota	263	161	0
All Others	84	702	0

Table 8: $1,000 Price Discount for GM Pickups with Best Price-Responses

Month	Chrysler	Ford	GM	Toyota	All Others	Outside
Total unit sales: difference between data and counterfactual						
6	4,664	6,682	24,815	297	-934	
7	2,296	4,153	-1,857	107	-1,126	
8	-1,178	-1,997	-1,952	-316	-1,001	
9	-1,209	-2,150	-1,943	-367	-1,108	
10	-1,226	-2,225	-2,124	-352	-1,161	
11	-1,208	-1,958	-2,162	-373	-1,201	
12	-1,374	-2,349	-2,021	-402	-1,368	
Total	766	157	12,756	-1,405	-7,898	-4,376

Table 9: Comparing flows with and without best-price responses

	Chrysler	Ford	GM	Toyota	All Others
Units					
no b.p.r.	-4,026	-7,187	19,580	-1,180	-5,026
b.p.r	766	157	12,756	-1,405	-7,898
Revenue (*thousands $*)					
no b.p.r.	-92,277	-173,548	319,603	-27,946	-91,820
b.p.r.	-16,485	-78,608	152,174	-44,678	-153,348

Table 10: 2002 Model Year Sales and Revenue with and without Incentives

Month	Unit Sales (thousands)			Revenue ($ million)		
	Data	CF	cdiff	Data	CF	cdiff
1	496	504	8	12,243	12,599	356
2	1122	1126	12	27,591	28,160	925
3	1092	1097	17	27,641	28,225	1,510
4	1175	1195	37	29,957	30,864	2,417
5	1035	1034	36	25,257	25,643	2,802
6	1238	1230	28	29,583	29,885	3,104
7	1431	1443	40	33,895	34,664	3,873
8	1368	1377	49	31,845	32,514	4,542
9	1421	1418	46	32,808	33,243	4,977
10	1433	1423	36	32,656	32,964	5,286
11	1403	1326	-41	32,214	31,179	4,252
12	1466	1343	-164	33,485	31,525	2,292

note: CF stands for counterfactual where automakers collude by not offering any incentives, cdiff for cumulative difference

Conclusion

- With motor vehicles, have a excellent opportunity to measure temporal substitution
- Find consumers are price sensitive and willing to substitute temporally
- Temporal substitution is by far the main force in consumers' substitution patterns
- With temporal substitution, accounting for dynamic pricing strategies is important. When not accounting for best price-responses, we overestimate revenue gains from temporary sales by 50%
- Automakers take advantage of consumers' ability to temporally substitute and price discriminate.

Table 11: 2002 Model Year Average Prices With and Without Incentives

	Months within the Automotive Model Year					
	1	2	3	4	5	6
Price	30,083	29,942	31,118	31,007	30,662	30,224
Price w/o inc	30,397	30,306	31,483	31,367	31,068	30,623
(diff)	-314	-364	-365	-360	-406	-399
	7	8	9	10	11	12
Price	30,017	29,915	29,768	29,340	28,926	28,608
Price w/o inc	30,366	30,275	30,167	29,763	29,566	29,391
(diff)	-349	-360	-399	-423	-640	-783

Table 12: Estimated coefficients from price discount regression model

parameter description		estimated	std err
Chrysler	no lag (ι_1)	0.492	0.123
	1 lag (κ_1)	0.277	0.123
Ford	no lag (ι_2)	0.513	0.125
	1 lag (κ_2)	0.305	0.131
Nissan	no lag (ι_3)	0.008	0.254
	1 lag (κ_3)	-0.345	0.266
Toyota	no lag (ι_4)	0.269	0.123
	1 lag (κ_4)	0.156	0.129
All others	no lag (ι_5)	0.046	0.181
	1 lag (κ_5)	0.737	0.189
Model year trend	ρ	-9.868	5.777
Inventories	ω	0.004	0.003